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## Random Utility Models of Pedestrian Crowd Exit Selection Based on SP-off-RP Experiments

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### Abstract

Detailed understanding of the factors based on which individual pedestrians select an exit in a confined area, is of crucial importance in modelling crowd movement. Lack of explanatory disaggregate data representing the relative importance of the latent factors contributing to exit decision, continues to be obstacle to tackle the problem. The full benefit of the state-of-the-practice class of choice data collection methods has not been derived in crowd modelling yet. This work discusses results of experiments recently conducted utilising SP-off-RP method of choice data collection. Standard and random-coefficient logit models were estimated to obtain an understanding of individual pedestrians' preference.

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**Keywords:** pedestrian crowd; exit choice; evacuation; random utility models; stated choice data

### 1. Introduction

In recent years, there has been a growing recognition of modelling pedestrian behaviour in several disciplines, notably in transport studies. There is a general consensus that safe and efficient design of public transport facilities and mass events require a solid knowledge of individual pedestrians' behaviour. As a result, gaining an accurate understanding of crowd pedestrian walking and decision-making behaviour has been of growing interest in the literature. The importance arises from the fact that development of models, which can sufficiently explain large crowd movement, is reliant on a fair understanding of individual pedestrian's decision process. Particularly, detailed understanding of the factors based on which individual pedestrians select an exit in a confined area, is of crucial

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importance in modelling crowd movement. However, lack of explanatory disaggregate data representing the relative importance of such latent factors, continues to be obstacles to tackle this problem.

As in many other decision-making modelling problems, the main difficulty in gaining this knowledge is that there is no easy and reliable method to directly observe or analyse the subconscious mental process, which motivates decision makers to decide for one or another available option. The problem can become even more complex when considering agents' demographic and environmental characteristics, emotional status (e.g. panic or emergency situations) or levels of congestion. Capturing this heterogeneity of taste within crowd population that translates to different behaviour is a major challenge.

To address the aforementioned issue, numerous studies have been conducted in pedestrian crowd modelling area, primarily focusing on development of walking-behavior models. The goal of most of these studies is to represent pedestrians' local adaptive behavior within the dynamism of their immediate environments ("what-is-the-next-step" models) (Helbing et al. (2000); Antonini et al. (2006); Campanella et al. (2009)). A subset of the studies, however, view the problem from a higher-level perspective and has focused on developing models that represent the next point (like an exit or (intermediate) destination) or general direction along which pedestrians desire (or are most likely to decide) to move. Although rather subjective, this view is sometimes referred to as "strategic" level of pedestrian decision in the literature (D. Duives and Mahmassani (2012)). To our knowledge, however, far less attention in the literature has been paid to recently-mentioned class of models compared to the walking-behaviour models, even though for any pedestrian crowd model to be able to sufficiently simulate complex facilities, there must exist at least some decision criteria. Obviously, the level of realism in the total modelling process is also affected by the accuracy of such decision criteria. This highlights the need to collect reliable disaggregate choice data to provide a better understanding of the underlying factors which influence pedestrian decision-making process when choosing an exit to egress a confined area.

Despite the miscellaneous models developed in the context of crowd pedestrian modelling, one major challenge has always been the lack of accurate explanatory data to estimate and calibrate the models either for local "walking-behaviour" models or for the so-called "strategic" decision levels (such as exit-choice models). Accordingly, significant research has also been conducted on pedestrian data collection techniques with the aim of estimation, calibration and validation of theoretical models, from collecting data by human experiments (Zhang et al. (2008), Heliövaara et al. (2012)), stated choices and virtual-reality decision data (Lovreglio et al. (2014)), and experiments with biological entities (Dias et al. (2013), Shiwakoti et al. (2011)) to video-processing techniques of analysing pedestrian movement (Hu et al. (2013), Hoogendoorn et al. (2004)). In this regard, we believe there is still a knowledge gap with regard to the provision of disaggregate pedestrian choice data.

This study aims to address the abovementioned problem. We believe that random-utility class of econometrics models can provide a well-established ground to develop models that can help represent pedestrian behaviour and/or ameliorate accuracy and flexibility of the existing methods. Recently, there are examples in econometrics literature, where innovative approaches of stated choice data collection have also been introduced, in which SP experiments are designed with a reference to an alternative in person's actual choice set. Referred to the real situation in which the respondent has recently been involved, such setting is designed to ameliorate the realism of preference elicitation and facilitate processing of experiments by respondents.

In this article, results of a recently-conducted pedestrian survey are presented. We have utilised a novel method of choice data gathering called "stated preferences off revealed preference" (SP-off-RP) (Train and Wilson (2008)) as well as a scoring data set of pedestrian exit selection at Monash University. Regular and mixed multinomial logit models have been developed based upon the mentioned data set.

The rest of the paper is organized as follows. In section 2 we take a selective look at the former studies conducted in crowd modelling area. Section 3 describes the survey, including the method of data collection, designed questionnaires and the scoring data. Section 4 is dedicated to illustrate the modelling result; and section 5 concludes and summarises the paper.

## 2. Literature Review

Crowd movement models can be categorised from different points of view. As stated before, they can be categorised as walking-behaviour models or ("tactical"-level) models of route or exit choice. In comparatively rare

cases, the model assimilates both modules of decision (Huang and Guo (2008), Hui and Ziyu (2010)). Crowd walking-behaviour models also consist of microscopic models, in which the movement decision of pedestrians is described at individual level and the total flow is modelled as the overall outcome of individual decisions. While this approach is more realistic in that it more sensibly reflects what happens in reality and allows integration of behavioural decision rules of individuals, it comes at the expense of computational efficiency and given the current computational power, is not easily scalable. As a result, alternative models have been proposed that consider the crowd movement as a flow, known as macroscopic models (Canca et al. (2013), Jiang et al. (2010)). Mixed or hybrid models that attempt to leverage both methods are also becoming more popular (Kneidl et al. (2013), Abdelghany et al. (2012)).

To represent the walking behaviour from a microscopic point of view, different approaches have been proposed and practiced by researchers ranging from force-based models (Helbing et al. (2000)) to different flavors of cellular automata models (Blue and Adler (2001)), heuristic methods (Bicho et al. (2012), Song et al. (2013)); and seldom random-utility-based models (Antonini et al. (2006)). Duives et al. (2013), or Zheng et al. (2009) provide a detailed analysis of the above-mentioned models.

To our knowledge, the full potential benefit of state-of-the-art random-utility techniques has not been practiced in the area of pedestrian modelling, nor have the novel approaches of data collection been applied so far. D. Duives and Mahmassani (2012) and Lovreglio et al. (2014) have studied exit choice behaviour using disaggregate stated choice data, that is compiled using internet based surveys. The former study has investigated the effect of angular deviation compared to distance, while the latter has studied the tradeoff between the number of people in the vicinity of each exit as well as in the vicinity of the agent, and the position of pedestrian (a proxy measure of distance). In both aforementioned studies, hypothetical binary exit scenarios have been designed.

### 3. Survey and Data Collection

To elicit the relative importance of the underlying factors, which may contribute to peoples' exit decision when evacuating or egressing a facility, a paper-based interview survey was conducted at Monash University, Clayton Campus in March and April 2014. The survey consists of two parts. The first part was intended to provide a general understanding with regards to the contributing factors which might affect pedestrian decision and the second part aimed to elicit the relative weights associated to these factors in a quantitative fashion through stated choice data.

The data was collected using face-to-face interviews with 52 (23 males and 29 females) interviewees, who were seen to exit "Robert Menzies" building (floor plan is shown in Fig 2.) towards campus centre. The interviews were carried out between 12:00 p.m. and 2:00 p.m. of working days, to coincide with busiest time when most people walk through the building to access the campus. Interviewees were also chosen among those, who were observed to have experienced at least a certain level of congestion and delay when coming out of one of the four available exit doors. Each interviewee's participation was appreciated by a small amount of monetary incentive (\$5) paid by cash at the end of the interview.

#### 3.1. Scoring data

Once interviewees were introduced to the survey, its purpose and also were informed of the monetary incentive, they were asked to score (rate) from 0 (absolutely unimportant) to 5 (highly significant) the proposed factors in terms of their significance on the exit decision that they just made to come out of the building. The factors offered to the respondents are as follows: (a) distance to each exit, (b) congestion around each exit, (c) visibility of each exit, (d) having formed a habit to depart through a particular exit, (e) following other pedestrians heading towards a particular exit, (f) Avoiding turning, (g) avoiding opposite flows (i.e. pedestrians who are walking in the opposite direction), (h) proximity to the destination.

It should be noted that, due to numerous reasons, the scoring data merely provides a general understanding of the relative importance of the proposed factors and cannot be regarded as a method for quantifying relative contribution of the factors. For instance, people may have different perception of the rates (0-5) presented to them. Also, they might consider two factors (for example, congestion and distance) quite important and rate them both as highest,

while facing the decision, they would prefer one to the other. In such a case, the margin of preference between these factors cannot be obtained from scoring data. Overall though, the scoring data can still provide a primary and general vision to the problem.

The results obtained from this part of the survey have been summarised in Fig. 1 (a)-(h), where the frequency percentage of each score assigned to each of the above-mentioned factors are represented. As illustrated, “avoiding turning”, “following” and “habit” turned out to be the least important factors, whereas “distance”, “congestion” and proximity to “destination” as expected received the highest scores. The factors of “visibility” and “opposite flows” also received relatively high rates.

### 3.2. Choice data

Information about people’s choice can be obtained through two traditional sources: stated preferences (SP) and revealed preferences (RP) data. The latter provides information about decision makers’ actual choice in their real choice situations, while the former elicits information through introducing choice scenarios to decision makers. Pros and cons of each type of choice data has broadly been discussed in the literature (Hensher, 2006). Simply speaking, RP data can be the analyst’s best option when the actual “market share” of alternatives is of the main concern, while SP data would be the proper approach when the modeler is mainly investigating the relative contribution of different factors (explanatory variables) on decision makers’ choice or is concerned about the situations in which new alternative(s) or attribute levels are going to be offered to the market.

It has been shown that through combining sources of preference data, one can achieve a certain more level of modelling benefits than can be obtained using each individual data source (Hensher (2008)). However, there are still situations in which RP data is either not accessible or is so ill-conditioned that it does not offer the modeller the level of information and variability required to exploit people’s preferences in a reliable fashion. Accordingly, studies have been conducted to ameliorate the realism and reliability of SP data while still enjoying the tractability of SP approach. One method, which has been of econometrics researcher’s growing interest is designing SP experiments based upon a reference alternative in people’s real choice set (Rose et al. (2008)). Train and Wilson (2008) have proposed the method called SP-off-RP in which the stated choice scenarios are designed with reference to the decision makers’ revealed choice. The respondents’ actual choice is asked or observed and then hypothetical scenarios are constructed and introduced to the same decision maker by deteriorating one (or more) attributes of their chosen alternative and/or ameliorating one (or more) attributes of their non-chosen alternative and they then are asked whether they still would choose the same alternative as they did in their real case or they would shift their choice to one of the other alternatives. Referred to the real-case scenario, the method is supposed to engender more realism as having experienced a similar situation, the respondents are more likely to relate to the hypothetical scenarios and process them with more precision. The choice-based nature of the sampling, however, would carry forward heterogeneity to the choice data. Train and Wilson (2008) have proposed a modified estimation process to capture this heterogeneity using the information of the agent’s RP choice.

We have applied the SP-off-RP method of choice data collection to elicit people’s relative preferences when choosing the exit door. Associated with each exit door of the building, different questionnaires were designed in which the following factors were varied over 14 hypothetical choice scenarios: distance to each exit, congestion (density) around each exit, visibility of the exit, and flow (of pedestrians) towards each exit. Three levels of distance, three levels of congestion, two levels of visibility (visible or invisible) and two levels for flow to each exit were considered to design choice scenarios. Each interviewee was introduced to the special questionnaire designed according to their RP choice in which the level of congestion around the exit that he/she has come out of was worse than all other exits in all scenarios. They were then asked if they would still choose the same exit door as they just did or they would shift to another alternative as the levels of attributes varied over choice experiments. Fig. 2 illustrates one sample of the hypothetical choice scenarios. In some experiments, exits 3 and 4 were assumed to be invisible from the decision maker’s hypothetical position. Corresponded to each “invisible scenario”, we designed another scenario in which we had updated the agent’s position in such a way that exits 3 and 4 (and accordingly the density around them) were visible, *ceteris paribus*. We attributed the congestion levels of exits 3 and 4 in such scenarios to their corresponded “invisible scenarios”.

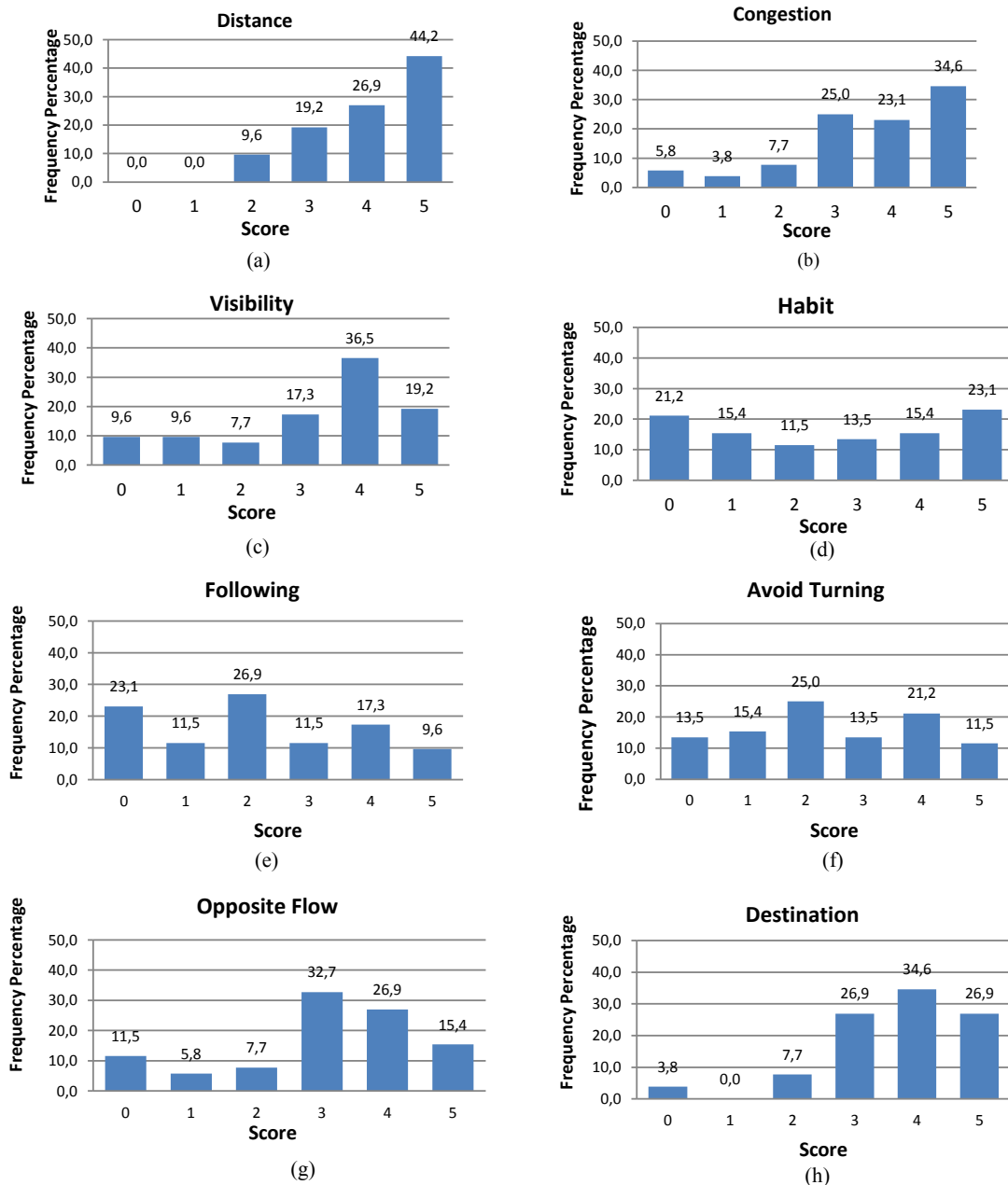
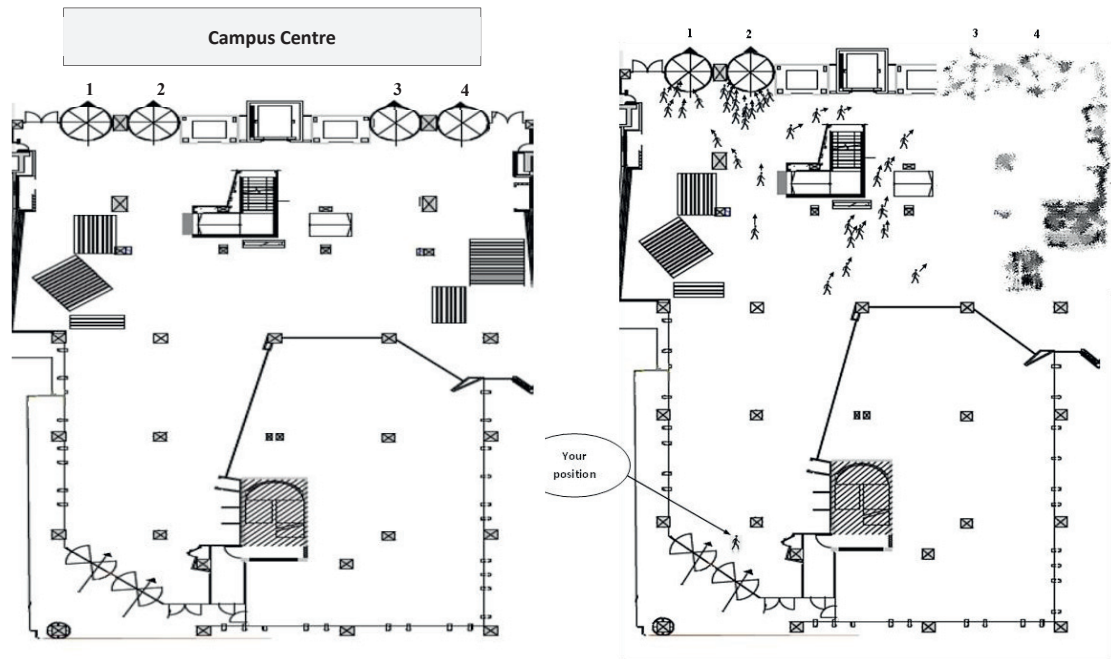


Fig. 1. frequency percentage of scores given by respondents to different factors influencing exit decision.

The primary reason for exclusion of other variables (mainly “opposite flow”) in designing the scenarios is to keep the number of scenarios as few as possible. It is important to note that the number of scenarios required to obtain the information that the modeler needs to elicit from the data dramatically increase with the number of attributes (variables). We chose the variables in designing hypothetical experiments that we believe (and the scoring data confirmed) are most important for evaluation.

In theory, when estimating models based on SP-off-RP data, the RP choices may either be maintained or dropped. Irrespective of this, the modification of the estimation process proposed by Train and Wilson (2008) to

address heterogeneity uses the information of RP choices made by the same decision maker. In our survey, the RP choices were recorded, however, due to the ambiguity of the exact moment, when the decision has been made, the attribute levels according to which each decision was made were by no means well-conditioned. This made us not to be convinced to use the modified estimation method. As a result, we dropped the RP choices from our estimation and used the normal estimation procedure, assuming exogenous sample. In other words, we limited ourselves to make use of the novelty of the data collection method, which will provide more realism in choice responses. Still, we acknowledge that the severity of the impact this assumption (exogenous sample) on our modelling results needs to be further scrutinised.



(a) Floor plan of Menzies building

(b) sample choice scenario corresponded to exit door 2 (congestion around exits 3 and 4 have not been represented due to the invisibility of the exits in the current decision maker's position)

Fig. 2 floor plan of Robert Menzies building and a sample choice scenario.

#### 4. Modelling Results

To quantify the relative contribution (weight) of different factors influencing pedestrian decisions when evacuating a place, multinomial logit (MNL) and mixed logit (ML) models were estimated based upon the choice data set described earlier. Random utility of alternative  $i$  ( $i = 1, 2, 3, 4$ ) for decision maker  $n$  ( $n = 1, 2, \dots, N = 52$ ) in hypothetical choice experiment  $t$  ( $t = 1, 2, \dots, T = 14$ ) is specified as Eq. 1, where  $\beta$  represents the vector of utility coefficients specified as Eq. 2, in which "ASC", "DIST", "DENS" and "FLTOEX" respectively signify "alternative-specific constant", "distance to each exit", "density around each exit" and "flow towards each exit", and utility coefficients specified as Eq. 2, in which "ASC", "DIST", "DENS" and "FLTOEX" respectively signify "alternative-specific constant", "distance to each exit", "density around each exit" and "flow towards each exit", and



“VIS” is a binary dummy variable which has set to be 1 when the exit is visible for decision maker and 0 otherwise, and  $\mathbf{X}_{nit}$  denotes the vector of associated variables (attributes). The error term,  $\varepsilon_{nit}$  is assumed to be identically and independently (over  $n$ ,  $i$  and  $t$ ) distributed as standard extreme value type I distribution (Eq. 3).

$$U_{nit} = \boldsymbol{\beta}^T \mathbf{X}_{nit} + \varepsilon_{nit} \quad (1)$$

$$\boldsymbol{\beta}^T = (ASC, DIST, DENS, VIS, FLTOEX) \quad (2)$$

$$f(\varepsilon_{nit}) = \exp(-\varepsilon_{nit}) \exp(-\exp(-\varepsilon_{nit})) \quad (3)$$

For MNL specification,  $\boldsymbol{\beta}$  is assumed to be a vector of constant coefficients (to be estimated) whereas for our ML estimation, the elements of  $\boldsymbol{\beta}$  (except ASC's) were assumed to be independently distributed as normal random variables with density  $G(\boldsymbol{\beta})$  (whose means and standard deviations are to be estimated). Such specification not only implicitly relaxes the restrictive assumption of independence from irrelevant alternatives (IIA) imposed by MNL model but also captures the potential random taste heterogeneity distributed over the population of decision makers. Choice probabilities corresponded to MNL and ML models are shown in Eq. 4 and Eq. 5 respectively.

$$P_{nit} = \exp(\boldsymbol{\beta}^T \mathbf{X}_{nit}) / \sum_{j=1}^I \exp(\boldsymbol{\beta}^T \mathbf{X}_{njt}) \quad (4)$$

$$P_{nit} = \int_{\boldsymbol{\beta}} [\exp(\boldsymbol{\beta}^T \mathbf{X}_{nit}) / \sum_{j=1}^I \exp(\boldsymbol{\beta}^T \mathbf{X}_{njt})] G(\boldsymbol{\beta}) d\boldsymbol{\beta} \quad (5)$$

The likelihood function to be maximised during the estimation process has been specified as Eq. 6, where  $\alpha_{nit}$  is a 0-1 dummy which equals 1 only if person  $n$  has chosen alternative  $i$  in choice situation  $t$ . Having been specified like that, the ML model would capture the serial correlation which is likely to be present in choices made by each individual. Serial correlation over repeated choices cannot be addressed by MNL model no matter if the likelihood function has been specified to represent panel data or not, but through generation of same random draws of distributions of coefficients for the choices made by each individual respondent, ML model is capable of capturing the problem. The goodness-of-fit measure, known as McFadden pseudo  $\rho$ -squared, has also formulated in Eq. 7 where  $LL(\cdot)$  signifies the log-likelihood function.

$$L(\boldsymbol{\beta}) = \prod_{n=1}^N \prod_{t=1}^T \prod_{i=1}^I (P_{nit})^{\alpha_{nit}} \quad (6)$$

$$\rho^2 = 1 - LL(\boldsymbol{\beta}) / LL(\mathbf{0}) \quad (7)$$

Estimation results have been shown in Tables 1 and 2. As can be seen, for both models the sign of coefficients are in accordance with our prior expectation and almost all estimates are statistically significant at 99% confidence level. According to the estimates signs, the more congested an exit or the further the exit is located to the decision maker, the less is the probability of that exit to be chosen. The model, however, explores the quantitative trade-off between those factors. In addition, when visible, the exit has more chance to be chosen than not being visible. The goodness-of-fit measure for both models are fairly large, although the ML model demonstrates a considerably better fit to the data, which can be an indication of the presence of random taste heterogeneity and/or serial correlation in the choices made by the respondents. The presence of taste heterogeneity over population of respondents is also further confirmed by statistical significance of standard deviations for random coefficients of ML. This provides a clear sign that people are having different tastes (attitudes) towards the factors introduced to them in choice experiments and hence, there is indeed a distribution of this taste over the population.

The only coefficient that poses an exception and its estimated value did not proved to be statistically significant is FLTOEX. It should, however, be noted that significance of an estimate is affected by two factors: the estimated value itself and the standard error of the estimate. High values of standard errors may give rise to insignificant estimates and so does close-to-zero values of the estimate itself. According to the results, the latter is the case in our model. As can be observed, the coefficient for FLTOEX has been estimated with the lowest standard error (highest

precision) compared to all other estimates. However, as the value of estimate itself is highly close to zero, the null hypothesis of the coefficient being equal to zero cannot be rejected at any of the commonly acceptable levels of significance. The interviewer experienced this in the field through the comments made by the respondents when making the choices. In reaction to changing the level of FLTOEX, some of the respondents would express: “these people might know something that I do not, so I might follow them” as a supplementary comment on their own choice (specifically in invisible cases) and some would say: “By the time that I get there, they may have already caused a congestion in front of the door so I will not follow them”. This is exactly what we have been referring to as taste heterogeneity. This has been formally reflected into our model estimation in the way that was described before. The mean for FLTOEX coefficient has got the same situation in ML model as it does in MNL model, whereas the standard error is statistically significant at 99% confidence level. Simply speaking, this result indicates that people are diverse with respect to this variable and the diversity is almost 50-50.

Table 1. Results for MNL model estimation.

Coefficient	Estimate	Standard Error	t-stat	p-value	95% Confidence Interval	
DIST	-.27114***	.03579	-7.58	.0000	-.34128	-.20100
DENS	-3.10295***	.24385	-12.72	.0000	-3.58088	-2.62501
VIS	.72953***	.19937	3.66	.0003	.33877	1.12030
FLTOEX	-.01146	.01874	-.61	.5411	-.04819	.02528
ASC1	.80369**	.31885	2.52	.0117	.17876	1.42862
ASC2	1.26370***	.35652	3.54	.0004	.56494	1.96247
ASC3	1.35884***	.19524	6.96	.0000	.97619	1.74150
ASC4	0 (fixed value)	----	----	---	----	----
McFadden pseudo $\rho^2 = 0.246$						
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.						

Table 2. Results for ML model estimation.

Coefficient	Estimate	Standard Error	t-stat	p-value	95% Confidence Interval	
Means of random coefficients in utility functions						
DIST	-.39053***	.05180	-7.54	.0000	-.49206	-.28899
DENS	-4.58003***	.47810	-9.58	.0000	-5.51710	-3.64296
FLTOEX	-.03857	.03083	-1.25	.2109	-.09900	.02185
VIS	1.10456***	.26984	4.09	.0000	.57569	1.63344
Nonrandom coefficients in utility functions						
ASC1	1.22248***	.39586	3.09	.0020	.44661	1.99836
ASC2	1.41044***	.44072	3.20	.0014	.54664	2.27424
ASC3	1.78973***	.23368	7.66	.0000	1.33172	2.24774
ASC4	0 (fixed value)	----	----	---	----	----
Standard deviations of random parameters						
DIST	.14110***	.03602	3.92	.0001	.07050	.21170
DENS	2.24059***	.34152	6.56	.0000	1.57122	2.90997
FLTOEX	.16281***	.03260	4.99	.0000	.09891	.22670
VIS	.98557***	.27287	3.61	.0003	.45076	1.52038
McFadden pseudo $\rho^2$ =0.298						

## 5. Summary and Conclusion

Random-utility models of pedestrian exit choice were estimated in this study using a state-of-the-practice method of choice data collection known as SP-off-RP. A combination of variables, not already been investigated in the literature, was studied through designing hypothetical choice experiments and their relative contribution to decision were quantified by estimation of MNL and ML models. Even though the choice data was not very large, it offered quite promising and sound results in terms of modelling quality. This could be regarded as a sign that the utilised



method of choice data collection does work in this context. One question that would be interesting to investigate in future studies is whether the SP-off-RP method of data collection has statistically brought more precision to overall modelling than pure SP data, and also if the combination of the two approaches would lead to better results.

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